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Research Article

Dynamic and Static Handwriting Assessment in Parkinson's Disease: A Synergistic Approach with C-Bi-GRU and VGG19

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Abstract: Parkinson's disease (PD) is a neurodegenerative disorder causing a decline in dopamine levels, impacting the peripheral nervous system and motor functions. Current detection methods often identify PD at advanced stages. This study addresses early-stage detection using handwriting analysis, specifically exploring the PaHaW dataset for pen pressure and stroke movement data. Evaluating online and offline features, the research employs pre-trained CNN models (VGG 19 and AlexNet) for offline datasets, achieving an overall accuracy of 0.53. For online datasets, velocity, and acceleration features are extracted and classified using Gated Recurrent Unit (GRU), Long Short-Term Memory (LSTM), and recurrent neural networks (RNN), with GRU yielding the highest accuracy at 0.57. Notably, the convolution-based model C-Bi-GRU surpasses other architectures with a remarkable 0.75 accuracy, emphasizing its efficacy in early PD detection. These findings underscore the potential of handwriting analysis as a diagnostic tool for PD, contributing valuable insights for further research and development in medical diagnostics.

Keywords: Handwriting analysis; LSTM; Parkinson's disease; Medical diagnostics and machine learning; RNN.

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1. Introduction

Parkinson's disease (PD), among the spectrum of more than 600 nervous system disorders, emerges as a significant global health concern, particularly affecting individuals aged 50 and older. This neurological syndrome not only results in the impairment of neurons but also profoundly impacts motor functions, with manifestations such as tremors, rigidity, and bradykinesia[1], [2]. Additionally, PD presents a range of non-motor symptoms, including olfactory difficulties, sleep disturbances, anxiety, and visual impairments[3]. Likewise, the societal impact is further intensified by the substantial financial burden placed on patients due to the expensive diagnostic equipment traditionally employed for PD diagnosis, such as SPECT scans that assess dopamine levels in the brain[3]. Early disease detection provides a better opportunity to effectively control progression with medicine and therapies. Traditional diagnostic aids include costly and high-maintenance equipment like SPECT and MRI scans. SPECT scanning uses the radioactive tracer to evaluate the reduced amount of dopamine chemicals in the brain; it is much more expensive for the patient.

Lack of sufficient resources and an increased number of suspected patients make it difficult for practitioners to diagnose and treat the disease effectively. As a result, in most cases, due to the absence of a rapid and valid screening tool, PD is only properly diagnosed once it has matured to later stages. With the advancement of computer technology, detecting diseases in their early stages is easy. Several practitioners used image processing, pattern analysis, and signal processing techniques to detect PD in its early stages with handwriting data and to define the correlation between PD and healthy patients because brain disease directly impacts motor neurons and graphomotor skills. For example, in Micrographia, the patient's handwriting is small and cramped. In addition, tremors also affect handwriting because of the involuntary oscillating movement of one or more patient body parts. Bradykinesia is another symptom in which the patient's handwriting speed slows down.

This study aims to find new ways to detect and intervene early in PD. Subsequently, the research explores the potential of computer technology to analyze handwriting patterns non-invasively. Handwriting analysis is promising because it directly correlates with motor neurons and graphomotor skills. Several studies have collected data from digitizers, tablets, and hand-drawn shapes. The results show handwriting can be an early diagnostic tool for PD[4]–[6]. Moreover, distinguishing between Alzheimer's disease (AD) and PD remains a complex task, particularly in their early stages. However, computerized handwriting analysis provides a unique avenue for differentiation. While both diseases share some common symptoms, such as tremors, distinctive features emerge.

AD primarily affects speech and memory, and PD impacts thinking speed, motor neurons, and broader cognitive functions[7]. Convolutional Bidirectional Gated Recurrent Unit(C-Bi-GRU), brings the power of recurrent neural networks (RNNs) to the analysis, enabling the model to capture temporal dependencies and nuances in dynamic handwriting patterns. In addition, this is particularly crucial for understanding the progression of PD symptoms over time. On the other hand, VGG19, a convolutional neural network architecture, excels in image feature extraction, providing a foundation for static handwriting analysis. Similarly, improved Parkinson's disease-related handwriting analysis is possible with its ability to distinguish static image details. Likewise, the synergistic coupling of C-Bi-GRU and VGG19 enhances the model's ability to capture the evolving nature of Parkinson's symptoms but also ensures an assessment encompassing the details embedded in static handwriting patterns. Combining these two powerful neural network architectures, the study aims to create an accurate diagnostic tool for Parkinson's disease in computerized handwriting analysis for neurological disorders using machine learning. The primary research problems revolve around predicting early PD through handwriting analysis using machine learning. In addition, challenges include the need for clearer differentiation between PD and other neurological disorders and refining the sensitivity and specificity of machine learning models. Also, this involves taking into account and dealing with any external factors that could influence the accuracy of the results.

Furthermore, the proposed solution centers on advancing computerized handwriting analysis for improved PD detection using machine learning techniques. This involves refining existing methodologies by incorporating machine learning algorithms for more accurate pattern recognition. Additionally, the study aims to address specific challenges by considering additional features and refining the dataset used for analysis. Overall, the study seeks to contribute to the field by understanding the strengths and weaknesses of existing methods for PD detection. Moreover, by exploring computerized handwriting analysis, the research aims to propose refined approaches for enhanced accuracy in early PD diagnosis. Incorporating machine learning techniques and examining relevant datasets contribute to predicting early PD. Overall, the study aspires to offer valuable insights that can guide future research in the realm of PD diagnosis and contribute to the development of more accessible and effective diagnostic methodologies.

In the following sections, the study will explore related work on PD detection, including previous methodologies and advancements. Then, the study will discuss the proposed method, which uses machine learning techniques for handwriting analysis to diagnose early PD innovatively. After that, the study will cover data collection and experimentation details. Finally, in conclusion, the research will summarize the key findings and insights from the study.

2. Related Work

Degenerative nervous disorders affect many body activities, such as walking, running, writing, moving and cognitive function[8], [9]. Some diseases cannot be cured, but early diagnosis can help better manage the symptoms and progress of these diseases. Since handwriting analyses manage multiple cognitive issues, the practitioner began to consider that handwriting is a very effective tool for early predicting and assessing the subject's mental condition. Handwriting analysis and hand-drawing shape. Emerging research in the computer science field and handwriting has been reviewed in a range of literature, such as personality assessments, forensic analysis, crime scene investigation, DNA tests, fingerprint analysis, and psychological tests, including hand-drawn methods of evaluating patients' mental health. In this chapter, this study will discuss handwriting analysis and potential strategies for early Parkinson's prediction.

The detection and verification of the handwriting sample was an interesting application for Forensic Record Examiners (FDEs). In the case of two written samples, the author's verification is decided on whether the two samples come from the same person. Writer characterization from handwriting using global and local features; the combination of both features has enhanced the identification and evaluation rate. Another method is a codebook for writer characterization[10]. A codebook is a dictionary of visual features made up of diagrams or small parts of writing. Each language has a writing style, and a specific writing pattern is generally known as a codebook[11]. While recently, researchers focused on different demographic features for writers' characterization, these attributes include gender, age group, and handedness (right or left)[12], [13]. This research uses offline and online features to characterize healthy subjects and PD patients.

Most of the research on different brain disorders has also been done using several methods suggested by experts. In the case of PD, researchers include early-stage diagnostic approaches to the disease; PD patients are mentally or physically poor because the development of dopamine chemicals in the brain is decreasing, muscles are not functioning properly, and the person may be paralyzed. In 1817, the first time PD was described as 'Shaking palsy' by Dr. James Parkinson, he identified six samples, three of which he examined[14]. Moreover, three he observed from the streets of London. In the mid-1800s, Jean-Martin Charcot separated Parkinson's from multiple sclerosis and other disorders, i.e., tremors, and in the nineteenth century, the Unified Parkinson's Disease Rating Scale was developed. This scale defined the different levels of PD and practitioner diagnosis of Parkinson's through anticholinergic drugs. In the late 1900s, researchers focused on symptoms of PD (rigidity, bradykinesia, and tremors.) and reducing the Dopamine chemicals in the brain.

The standard approach uses MRI (Magnetic et al.) and CT or SPECT scans to diagnose the disease, but they only operate with doctors or skilled professionals. Moreover, in other medical therapies, Levodopa is also considered the gold standard for Parkinson's diagnosis. These medicines enhance dopamine to the remaining cells in the substantial ni- gra(levodopa medications), but all these techniques are pensive to the patient. With the development of computer technology and the golden age of AI, various approaches are used for PD. These days, the practitioner uses a non-invasive technique or procedure to examine PD without any skilled persons.

In 2013, B. E. Sakar et al. [15] used a non-invasive technique involving speech tests for the recognition of PD by using machine learning techniques. In 2014, researchers[16] worked with the Speech dataset, but the results of this research were not very useful for doctors because of voice changes due to flu or other diseases. However, several studies describe PD as directly impacting the graphomotor skills of persons. In literature, many researchers work on handwriting analysis for early prediction of Parkinson's but use different computerized systems for prediction. Various solutions have been developed over the years to diagnose PD and other related diseases, one solution being wearable devices attached to the patient's body. In 2011, they integrated their device into smart gloves[17]. In addition, this signal detects the severity of motor dysfunction in PD by smart gloves. It measures the movement of fingers when producing handwriting, making non-invasive techniques more useful and less expensive. Handwriting requires the participation of various body parts such as fingers and arms and also includes motor neurons; a healthy person manages the participation of all parts for the writing task; however, when this study performs a writing task for the patient, the motor neurons do not function properly. The different stages of patients with PD can be identified in all sequential values and give the classifier an emphasis on the output of sequential data analysis.

There are several models used for the classification of data and feature extraction. Classification is an important part of research because, evaluating the quality of the literature, this study provides the best results on this disease. In the literature survey, many techniques were used for classification. The most commonly used help vector machine is Naive Bayes and neural networks. Some researchers used a combination of classifiers and often used several neural networks to improve overall accuracy. In this study implementation, five classifiers are used: support vector machine (SVM), CNN, RNN, LSTM, and GRU. However, these classifiers are used in two ways: firstly, this study applies to online data, and secondly, to offline data. In the next section, the study will discuss the proposed methodology. The solution involves a detailed approach to predicting PD, considering online and offline features. The research will highlight the key contributions, showcasing how the study uses deep learning techniques such as neural networks and SVM classifiers to predict PD accurately. Overall, the goal is to provide a practical solution that improves the early detection and diagnosis of PD.

3. Proposed Method

This chapter introduces the proposed methodology for PD prediction; the previous chapter reflects the main contributions of this research, which describes online and offline features and gives different PD predictions using Deep Learning techniques. In this section, this study presents the proposed method used in this work, as shown in Figure 1.

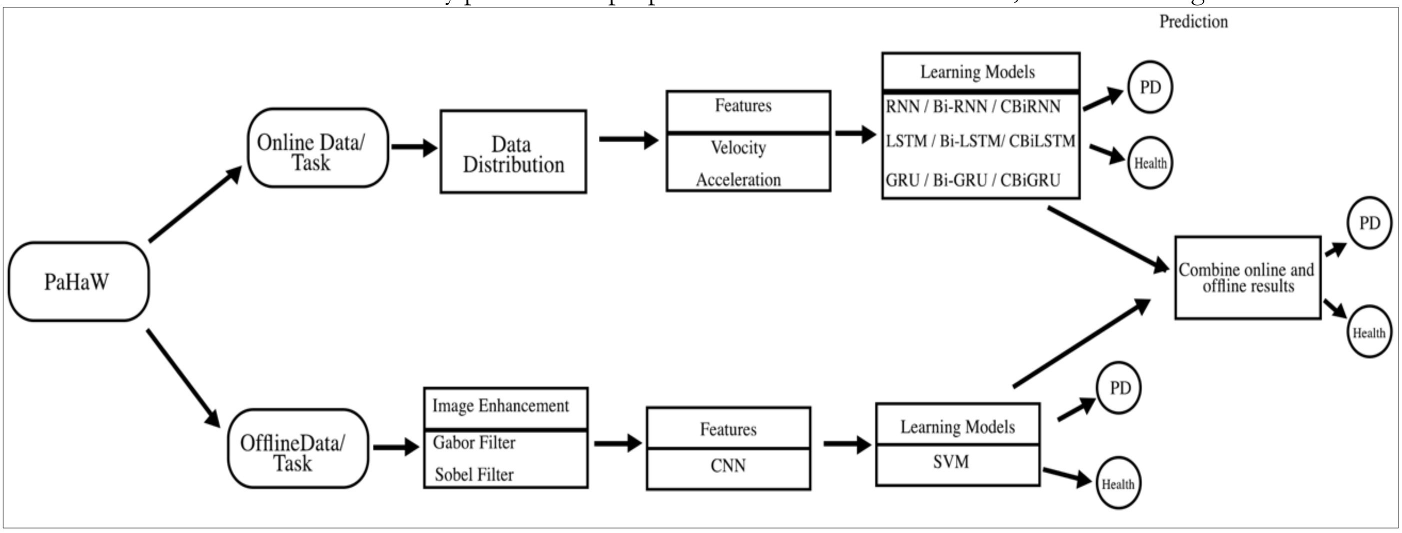

Figure 1. Proposed Method.

3.1 Dataset

Data acquisition is a very difficult task when it comes to medical problems. This research used the Parkinson's Disease Handwriting Dataset[4], see Figure 2 for a dataset sample. This dataset consists of samples from 37 Parkinson's patients (19 males and 18 females) and 38 healthy subjects (20 males and 18 females). All members involved in PD diagnosis enlist from the movement disorder center at The Department of Neurology, Masaryk University, and St. Annes Hospital in Smo, Czech Republic. All samples were written in the native language of the Participants, and the participants completed all tasks according to the template.

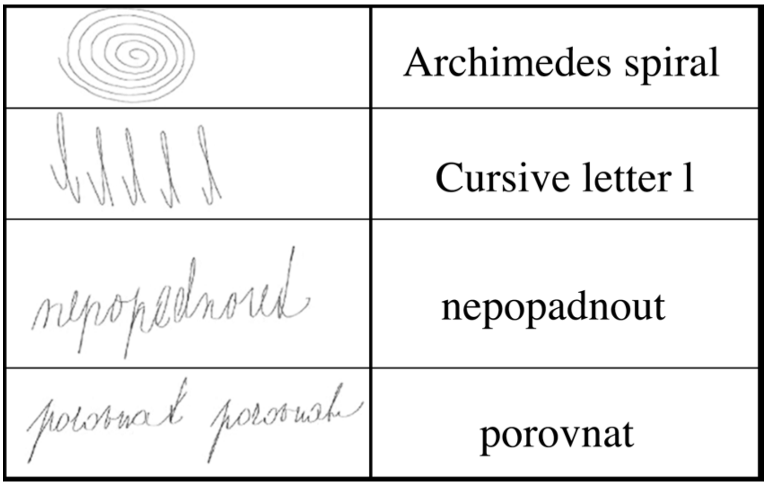

Figure 2. Sample of Dataset.

3.2 Data Preparation

The Acquisition Device discussed in the previous section collects the pen-based data. These included all functional attributes that could be used for the derived kinematics features. All of these features are sequentially measured within the same time intervals. In literature, authors mostly work with these sequential features and measure only mean values, then feed them to the model[4]. However, the beneficial information is lost when they transform the sequential value into a mean value. Therefore, this study uses all sequential values, gives the classifier as it is, and emphasizes the output of sequential data analysis. There are several models used for the classification of data and feature extraction. Classification is an important part of research because, by evaluating the quality of the literature, this study provides the best results on this disease. In the literature survey, many techniques were used for classification. Some researchers used a combination of classifiers and often used several neural networks to improve overall accuracy[18]. In implementation, this study uses five classifiers: SVM, CNN, RNN, LSTM, and GRU. However, these classifiers are used in two ways: firstly, this study applies to online data, and secondly, to offline data.

3.3 Offline Features in Parkinson's Disease Prediction

An in-depth investigation of studies utilizing offline features for PD prediction reveals the significance of static datasets, including images and handwriting samples. Convolutional neural networks extract features such as pressure, grip, tilt, and acceleration through the Static and Dynamic Spiral tests. These static features provide crucial insights into the characteristics of PD, with classifiers like SVM, Random Forest, and RNN achieving significant accuracies. Likewise, the static data analysis approach demonstrates the potential for accurate PD diagnosis by thoroughly examining spatio-temporal and statistical measures.

3.4 Parkinson's Disease through Online Feature Analysis

Online features play a crucial role in providing real-time insights for PD research. In addition, by utilizing devices like digitizers and conducting online experiments, researchers capture in-air movements, kinematic attributes, and pressure sensitivity. The continuous monitoring enabled by online feature extraction offers a dynamic assessment of PD symptoms. Moreover, classifiers such as SVM, discriminant analysis, and random forest showcase their efficacy, achieving considerable accuracy. In sum, combining online and offline feature extraction methodologies forms a comprehensive approach to PD prediction, catering to the dynamic nature of the disease while leveraging the richness of static datasets for accurate and timely diagnosis.

3.5 Features Extraction

In this section, the features are extracted and utilized, both from offline and online handwriting. These features are also discussed in a later section.

3.5.1 Online Features

Online features provide valuable information for the diagnosis of PD. This research is working on online features calculated from raw data in the PaHaW database. Various features include (x-y) coordinate, azimuth, altitude, pressure, time stamp, and button status. New features, such as velocity and acceleration, are derived using these features. New features are extracted by using 1D convolution in the PaHaW database.

3.5.2 Offline Features

In offline features, these features are derived by handwriting and hand-drawing. Some researchers used offline functionality instead of online attributes [19], [20]. In 2015, Pereira used a hand-drawing shape to extract the features. This case study used the Dortar et al. dataset. The original dataset contains online features extracted from the device (X, Y coordinates, button states, pressure), so this study can convert all online features to images. This work was also done in 2019. This study uses this idea for this research scenario [3]. The online features are in the form of numeric data and by plotting x and y coordinates into images.

3.6 Data Enhancement

3.6.1 Gabor Filter

The Gabor Filter is an orientation-sensitive filter used for texture analysis, which analyses the images containing any specific frequency information. It also points out the unique location in the localized and analysis regions. This filter strongly responds to the location of target images; in this research, the Gabor filter gives different responses to images when this study applies different banks of filters with different orientations and wavelengths. This study uses Gabor's equation with different parameters (gamma, wavelength). Figure 3 is the sample results of the Gabor filter effect.

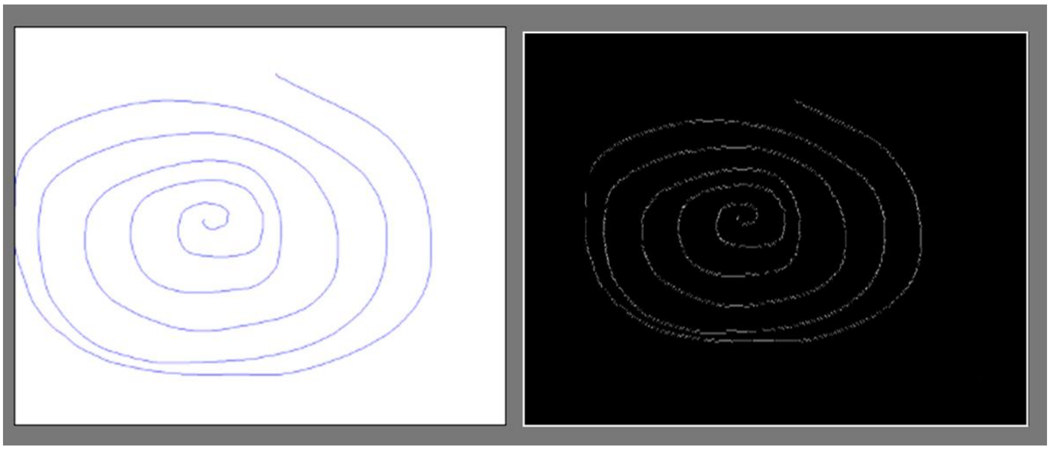

Figure 3. (**left**) Original Image; (**right**) Filtered Image (Gabor filter applied).

3.6.2 Sobel Filters

The Sobel filter, sometimes called the Sobel operator, is used in edge detection algorithms. In 2017, the Sobel filter was used for sickle cell disease to detect abnormal red blood cells[21]. Red blood cells in the form of a sickle are not flexible and can attach to the vessel wall, causing blockage of blood flow. Similarly, this study used the Sobel filter to detect edges through offline data and early prediction of PD. This study uses the Sobel mask equation for x and y since this mask is applied in both directions. Figure 4 is the sample results of the Sobel filter effect.

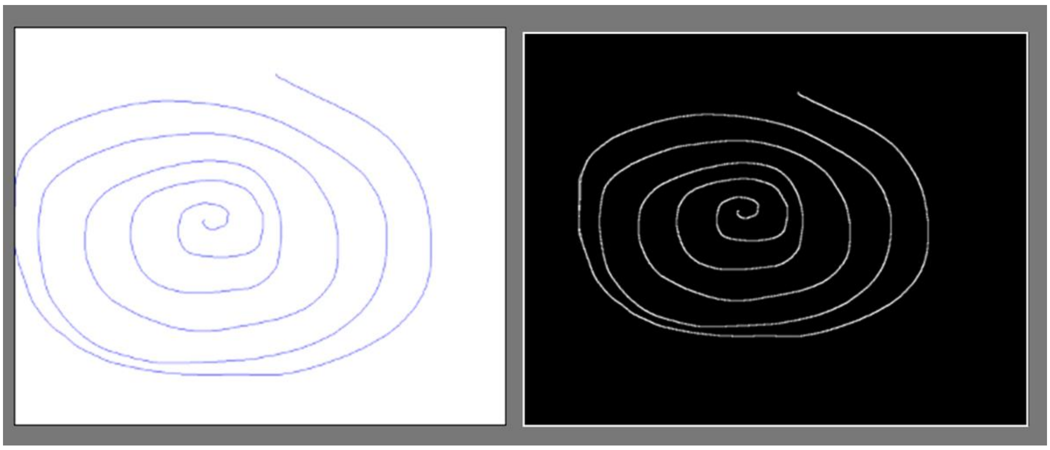

Figure 4. (**left**) Original Image; (**right**) Filtered Image (Sobel filter applied).

3.7 Convolutional Neural Network (CNN)

Convolutions Neural Networks The same as Artificial Neural Networks include loss functions, neurons, and other hyper-parameters[22]. The idea of CNN began after Alex-net in 2012; in Alex-net, 8-layer was used for classification, but in just 3 years, researchers moved from 8-layer to 152-layer Res-net. CNN has become the go-to model for every problem related to the image[23]. The common use of CNN is featuring extraction without any manually designed filter or human supervision. CNNs have three main layers: the Convolution layer, the pooling layer, and the fully connected layer.

1. Convolution Layer: This layer is used for extracting feature maps; this operation is performed by using the different kernel matrices to move on input images with different strides, and strides determine the amount of kernel(filter) and how many times they move on the input image[24].
2. Pooling Layer: The pooling layer prevents overfitting by reducing hyper-parameters and changing weight in the model. This layer reduces the size of each feature map to handle the complexity of the network.
3. Fully connected Layer: The third fully connected layer is used to classify each feature according to the problem of two-class problems. This study uses the sigmoid activation function, which uses softmax for many class problems [25]. In this study, a sigmoid activation function was used, and one dense layer at the end in which all neurons connected because this study has two classes, healthy and PD.

3.8 Recurrent Neural Network (RNN)

Recurrent neural network (RNN) is a modified form of Artificial neural network. Because of this memory, it enables them to transfer information along with the network. RNN copes with sequence problems, in which every layer represents a sequence of time steps performed the same task, and its output depends on previous Computation[26], [27].

3.9 Pre-trained Model and Transfer Learning

This research uses several models for feature extraction from three types of images: 1) original images, 2) Gabor-filtered images, and 3) Sobel-filtered images. This study uses transfer learning for small datasets because training data is less, which allows the network to train datasets to be adapted to another dataset. There are a series of pre-trained CNN models like Alex-net, VGG19, and Resnet in which each layer is connected with other layers; these models are listed below.

1. Alex-net: Alex-net is a further modification of Lenet. This model is trained on the ImageNet dataset. It consists of five layers of convolution and three fully connected layers. This study works with five convolutions but one fully connected layer and the last layer for classification, the image input size 227×227.
2. VGG19: VGG is introduced by the Visual Geometry Group at Oxford. This is a convolution neural network with 19 layers; two architectures of VGG are developed with 16 and 19 layers (convolution + fully connected), and this model has an image input size of 224×224.

Moreover, in the process of refining the proposed method, careful attention was devoted to the optimization of hyperparameter settings. Parameters such as learning rates, batch sizes, and regularization terms had systematically adjusted to balance model complexity and generalization ability. Likewise, fine-tuning iterations involved a rigorous evaluation of validation datasets, with subsequent adjustments based on empirical results. Adopting a systematic approach improved the model's performance across tasks.

4. Data Collection and Experimentation

This section describes the specifics of all experiments, computes the efficiency of the different models, and examines the effectiveness of extracted features that help assess PD's presence and absence. In this section, this study first discussed training and testing data and then showed results using Deep Learning Model and Image Processing techniques.

4.1 Training and Test Datasets

The PaHaW dataset contains 75 sample files, all of which are used for the experiment (37 Parkinson's patients and 38 healthy subjects). This study extracted the features (acceleration and velocity of x and y) from 75 samples, 80% of which are given to the training set and 20% to the test set. This study uses k-fold cross-validation techniques to Enhance the data because the dataset is insufficient to train. In this research scenario, this study divides 75 sample data 10-fold. 8-fold take as a training set and 2 for the test set after every rotation test file change. Using this technique, the model is trained with a new sample and tested with a new one.

Moreover, the study designed different tasks to evaluate the model's performance in recognizing specific patterns. The Archimedean Spiral task assessed the model's ability to understand and reproduce a distinct geometric pattern. Tasks labeled Repetitive(l), Repetitive(le), and Repetitive(les) aimed to test the model's proficiency in handling repetitive sequences with varying degrees of complexity. Subsequently, moving into linguistic patterns, the Word (leplorka), Word (porovnal), and Word(nepopadnoul) tasks evaluated the model's capability to recognize and generate sequences based on specific words. These tasks assessed the model's adaptability across diverse pattern types, encompassing geometric and linguistic structures.

4.2 Online Experiment Results

In the first experiment, a simple deep-learning model is applied to every task for classification without using directional scenarios and convolution, and The results are detailed in Table 1. This study discusses the task-wise result overall best accuracy on the first task because when a patient draws a spiral, the stroke is continuously connected with the surface. This task is easy for the patient; it is used for capturing essential tremors. Task 2-4 are repetitive tasks in which accuracy is higher on the GRU classifier using different hyper-parameters, so in this study, different authors give better accuracy on simple Machine learning models. Hence, this study performs a further experiment for better results. In the second experiment, Bidirectional Architectures are used for every task. Due to the small data size, this study uses 10-fold cross-validation to assess the robustness of the proposed technique. In this experiment, directional architecture helps enhance the result on this dataset. To increase the results and performance of the model, this study uses convolution with different models. When discussing task-wise accuracy, the first task shows the best accuracy on the GRU model, and the goal of this study was to achieve higher accuracy by using a gated recurrent neural network, an advanced merging technique. Other tasks show the best performance on LSTM. The sentence task is used to find fatigue in writing. However, this accuracy is below 50% on all models, so this study conducted more experiments on all tasks because accuracy is less than 50% in some tasks, and the model needs to be better. In the last experiment, 1D convolution was used to enhance the result, and the complexity of the RNN model also reduced and re-assessed the efficacy of Bi-GRUs in handwriting sequence scenarios. After using convolution for the tasks, 1-dimensional convolution achieves excellent raw data performance. All tasks data is divided into 10 folds and passed to the classifier. In 2-4 tasks (Repetitive(letter)), the minor changes the results since author[2] generates uniqueness in the tasks after one letter has also been enhanced and when this study addresses the word task with precision, comparatively, the same for all versions.

Table 1. Task-wise mean accuracy of the system.

Task	RNN	LSTM	GRU
Archimedean Spiral	0.55	0.66	0.77
Repetitive(l)	0.57	0.55	0.66
Repetitive(le)	0.47	0.85	0.85
Repetitive(les)	0.47	0.37	0.42
Word (leplorka)	0.32	0.42	0.28
Word (porovnal)	0.56	0.66	0.57
Word(nepopadnoul)	0.28	0.52	0.71
Sentence	0.28	0.42	0.42
Overall Accuracy	0.43	0.55	0.58

4.3 Offline Experiment Result

The original dataset (PaHaW) does exclude the images. The database contains the online attributes (x and y) coordinate, pen trajectory, and pen status. In 2019, study [3] worked on offline data and produced images by plotting the x and y coordinates in Figure 5. This study uses these images to classify healthy and PD subjects for further enhancement and learning. The feature extraction process is done by Alex- net and VGG19 and given to the network using an image processing filter for edge detection and enhancing the dataset to train the model. When performing the experimental task with CNN (Alex-net and VGG19), this study used only one fully connected layer (FC) and gave it to SVM for classification. Here, this study addresses all tasks. Precision is better for VGG19 in the first task because of its deep architecture. By default, its load weights are pre-trained on the image-net dataset, and in all tasks, accuracy is higher on a sentence task because of its complex patterns; Word and repetitive tasks display comparatively the same performance.

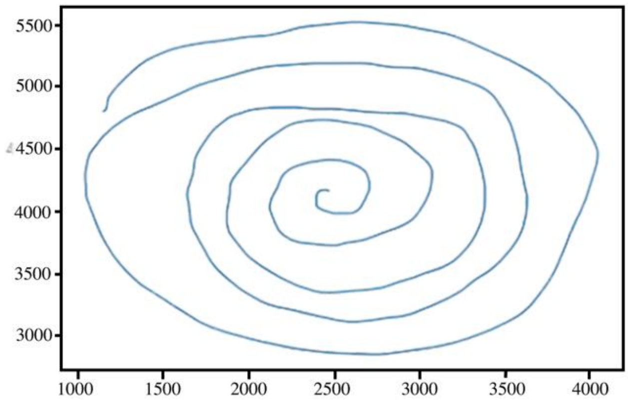

Figure 5. Plotted image.

4.4 Combination of Results from Online and Offline Features

This study will discuss the combination of online and offline results to establish the viability of the proposed model further. This study compares with the state-of-the-art presented in Figure 6. All studies have utilized the PaHaW dataset to assess the proposed method. The author[28] employed several dynamic, kinematic, and pressure features to train the neural networks. On the other hand, the researcher extracted CNN-based features by plotting the temporal information[3], in-air, and on-surface information of patients and health given in the PaHaW dataset. This study discusses the combined result of both online and offline results according to the most effective task in the PaHaW dataset; for comparison, the authors' accuracy is better than that of both authors. The tasks show different accuracy because stroke continuously draws the task in all directions, and dynamic changes can be better captured. The first and second tasks are the most handout tasks in this research; this task shows better accuracy than other studies. This sentence task has several dynamic patterns, which enhance its effectiveness, as reported in other studies in Figure 6. otherwise, word-based tasks ‘leplorka’ and ‘nepopadnoul’ show the relativity of the same results; conversely, the word task ‘porovnal’ obtained the highest accuracy. The one thing this study observed when this study employed the raw data recorded by the device was that the accuracy was lower. However, when this study worked with kinematic and offline features, the system's performance improved after combining both results. In Table 2, the study presents the system's task-wise mean accuracy without employing convolution. This analysis provides insight into the system's performance in various tasks without convolutional operations.

Table 2. Task-wise mean accuracy of the system without convolution.

Task	C-BiRNN	C-BiLSTM	C-Bi-GRU
Archimedean Spiral	0.57	0.63	0.80
Repetitive(l)	0.66	0.65	0.78
Repetitive(le)	0.68	0.85	0.66
Repetitive(les)	0.50	0.71	0.50
Word (leplorka)	0.42	0.45	0.42
Word (porovnal)	0.16	0.56	0.57
Word(nepopadnoul)	0.28	0.50	0.71
Sentence	0.28	0.42	0.42
Overall Accuracy	0.44	0.60	0.61

On the other hand, Table 3 showcases the task-wise mean accuracy of the system with convolution, offering a comparative evaluation against the non-convolutional counterpart. Likewise, including convolutional processes aims to highlight any improvements or changes in accuracy attributed to convolutional operations. Furthermore, Table 4 explains the task-wise system accuracy on offline data. Overall, this analysis of various tables provides a fine comprehension of the impact of convolution and system performance differences across task categories, offering valuable insights for future research. In addition, Figure 6 displays a graph depicting the task-wise best classification accuracies reported in the state-of-the-art. Moreover, in Drotar et al. [28], words (personal) and sentences showed good results, outperforming other tasks, with an overall accuracy of 0.69. However, in the Moetesum et al.[3], ArchimedeanSpiral showed good accuracy compared to other tasks with an overall accuracy of 0.61. Likewise, combined C-Bi-GRU + VGG19 outperformed with an overall accuracy of 0.82 in comparison to both other studies. In sum, the subsequent section provides a conclusion summarizing the key insights and findings drawn from the study.

Table 3. Task-wise mean accuracy of the system with convolution.

Task	C-BiRNN	C-BiLSTM	C-Bi-GRU
Archimedean Spiral	0.44	0.50	0.88
Repetitive(l)	0.52	0.60	0.66
Repetitive(le)	0.66	0.75	0.71
Repetitive(les)	0.52	0.73	0.74
Word (leplorka)	0.42	0.66	0.73
Word (porovnal)	0.33	0.60	0.80
Word(nepopadnoul)	0.32	0.66	0.61
Sentence	0.56	0.56	0.80
Overall Accuracy	0.47	0.63	0.74

Table 4. Task-wise system accuracy on offline data.

Task	Alex-Net Features	VGG19 Features
Archimedean Spiral	0.60	0.71
Repetitive(l)	0.64	0.49
Repetitive(le)	0.56	0.55
Repetitive(les)	0.66	0.72
Word (leplorka)	0.64	0.50
Word (porovnal)	0.49	0.66
Word(nepopadnoul)	0.54	0.80
Sentence	0.67	0.83
Overall Accuracy	0.60	0.66

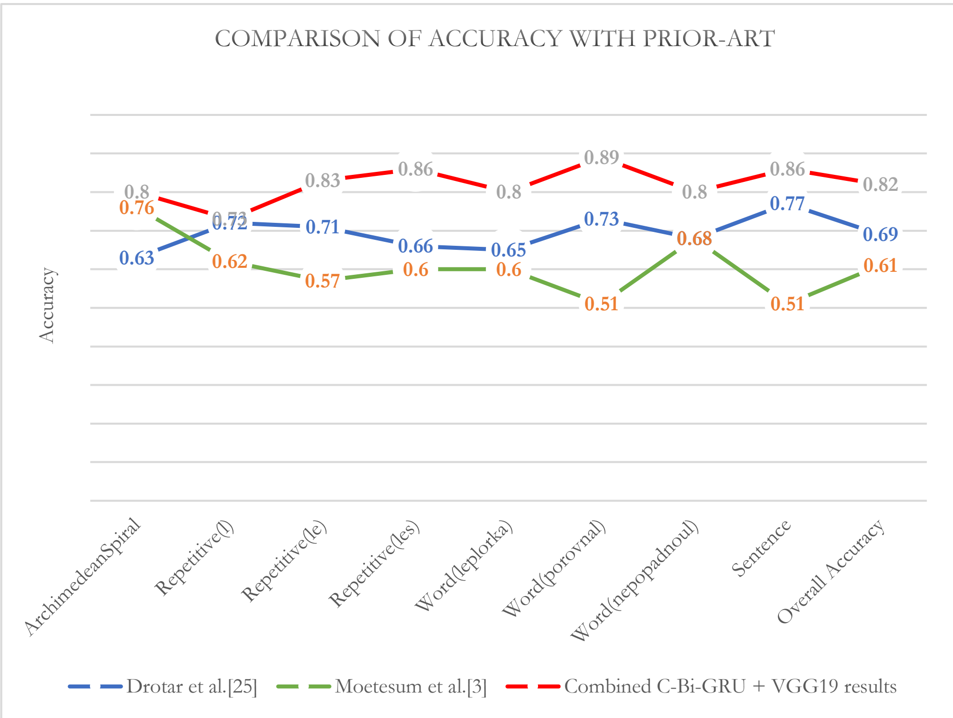

Figure 6. Graph of Task-wise best classification accuracy reported in the state-of-the-art

5. Conclusions

This study introduces the potential of handwriting attributes to predict PD. The literature has been investigating the kinematic, Spatio-temporal, and pressure features. However, this study combines online and offline features using various classifiers with one-dimensional Convolution and other classifiers (LSTM, RNN) but with the best accuracy on GRU. This study does not deny the research on online features. Rather, it enhanced the author's knowledge and showed the effectiveness of the offline features. This study is getting data augmentation by using different filters (Gabor, Sobel) on offline data. This information trained the model for classification. This study used the pre-trained model of CNN for feature extraction in offline data, and in online features, this study uses multiple deep learning classifiers. The result of this research experiment enhances the training time. The benchmark dataset PaHaW was used for research, and this study targeted PD prediction from handwriting. This system predicts many diseases, including Alzheimer's, Dyslexia, Dysgraphia, Autism, and other learning difficulties in children. The online recorded values were converted into images by plotting the pen trajectory. Another important aspect of this study is that it explores the image processing techniques to detect the noise recorded when they take samples of PD and healthy subjects. Evaluation on a standard dataset that reports an overall accuracy of 81% when this study combined both features. The performance measures across the multiple datasets will help guide this study in the direction of further research in the future.

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